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Exploring the relationships between different dimensions of digital transformation and corporate greenization: evidence from listed companies in China

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In recent years, there has been an increasing recognition of the importance of the coordinated development of digitalization and greenization. However, the existing research lacks a systematic framework for understanding the relationship between different dimensions of digital transformation and various strategies of green innovation. Furthermore, the role of different types of slack resources in this relationship has been largely overlooked. This paper aims to address these gaps by examining the impact of digital transformation on corporate greenization and the moderating role of organizational slack from a heterogeneity perspective. To achieve this, we differentiate digital transformation into two dimensions: breadth and depth. Similarly, corporate greenization is divided into input and output. Additionally, we distinguish between absorbed and unabsorbed slack resources. We empirically test our research hypotheses using data from Chinese A-share listed companies from 2011 to 2020. Our findings reveal the following insights: 1) The breadth and depth of digital transformation positively influence corporate greenization outputs, while negatively affecting greenization inputs. 2) The depth of digital transformation has a stronger impact on both greenization input and output compared to its breadth. 3) Absorbed slack resources and unabsorbed slack resources not only act as negative moderators in the relationship between digital transformation and greenization inputs but also weaken the positive impact of digital transformation on greenization outputs. 4) Absorbed slack resources exhibit a stronger moderating effect than unabsorbed slack resources. This paper contributes to the literature by shedding light on the differential effects of different dimensions of digital transformation on various types of greenization, considering the role of slack resources. Moreover, it provides practical implications for effectively advancing digitalization and greenization in Chinese enterprises.

KEYWORDS

breadth of digital transformation, depth of digital transformation, input of corporate greenization, output of corporate greenization, absorbed slack resources, unabsorbed slack resources

1 Introduction

The adverse effects of global warming and environmental pollution have had a significant impact on economic activities worldwide. Addressing these environmental challenges has become an urgent task for global economic development. In line with this, the Chinese government has demonstrated its commitment to reducing environmental pollution by announcing its goal to achieve a peak in carbon dioxide emissions by 2030 and carbon neutrality by 2060 during the 75th session of the United Nations General Assembly. At the same time, new technologies such as artificial intelligence, blockchain, cloud computing, and big data have elicited substantial changes in business operations and process control. This digital transformation has become a new engine for the high-quality development of micro-enterprises and macro economy, thereby occupying a pivotal role in the process of low-carbon transformation of the entire society. As the main entity responsible for environmental obligations and a key participant in digital transformation, the relationship between digitalization and greenization of enterprises has become a prominent topic in various disciplines, including information systems and strategic management.

The relationship between digitization and greenization is a complex and interdisciplinary issue that operates at multiple levels. At the national and industry levels, considerable attention has been given to the consequences of digitization, the antecedents of greenization, and how digitization influences greenization. Digitization refers to the process of transforming traditional societies into intelligent societies through the application of new technologies such as artificial intelligence and big data. It relies on digital platforms as infrastructure and digital data as a new energy source (Gradillas and Thomas, 2023). As a new driving force, digitization has a significant impact on various aspects of the economic system, including energy consumption (Wang and Su, 2020; Xu et al., 2022), economic growth (Myovella et al., 2020), food production (Lioutas et al., 2021), and manufacturing transformation (Papadopoulos et al., 2022).

Greenization, on the other hand, represents a development model that embraces environmentally friendly and sustainable practices to minimize negative environmental impacts while promoting economic growth (Wang et al., 2020). Existing literature has explored the driving factors of greenization from various perspectives, such as trade freedom and openness (Wang et al., 2023a; 2023b), natural resource rents and corruption governance (Adebayo et al., 2023; Li et al., 2023), and geopolitics (Wang et al., 2023c; Li et al., 2024). In comparison, the relationship between digitization and greenization has received less attention (Wang et al., 2023d) and consensus has yet to be reached. Some scholars argue that digitization can promote energy conservation and emission reduction through technological innovation (Ren et al., 2023) and energy infrastructure advancements (Murshed, 2020). However, other studies have found that digitization leads to increased resource and energy consumption, as well as waste and emissions from hardware manufacturing, use, and disposal, ultimately exacerbating environmental burdens (Chen et al., 2020; Lange et al., 2020). Additionally, some research suggests a nonlinear relationship between the digital economy and carbon dioxide emissions (Xiang et al., 2022b). Moreover, the impact of digitization on greenization is contingent upon globalization, as indicated by certain studies (Wang et al., 2023e).

At the enterprise level, research on the relationship between digital transformation and corporate greenization primarily focuses on three main aspects. The first aspect pertains to the measurement of core variables. Most studies in the literature consider digital transformation and corporate greening as overall activities of a firm, but there are a few studies that have divided these variables into different categories. For digital transformation, some studies propose four general transformation strategies by combining digital technologies with business models (Tekic and Koroteev, 2019), while others divide it into exploitation and exploration based on differences in business operations (Liu Q. R. et al., 2023), or into technology-based and market-based in terms of internal activity change and external environment adaptation (Ying and Jin, 2023). Regarding corporate greenization, existing literature often categorizes it as incremental and radical based on the pace of innovation activities (Klimas and Czakon, 2022), or process-related and product-related based on the economic benefits generated by green activities (Karimi Takalo et al., 2021), or substantive and strategic from the motivation for green transformation (He et al., 2023).

The second aspect focuses on exploring the relationship between the core variables. There is widespread debate in the literature regarding whether and how digital transformation affects green innovation. Some argue that digitalization promotes greenization through mechanisms such as easing financing constraints (Xue et al., 2022; Fan et al., 2023; Wang C. et al., 2023), attracting government subsidies (Feng et al., 2022; Xu et al., 2024), and improving capital investment and allocation (Liu X. et al., 2023; Yuan and Pan, 2023; Xu et al., 2024). Others suggest that digitization may hinder greenization by impeding knowledge sharing (Sun et al., 2021), creating tensions (Hellemans et al., 2022), leading to disruption risks (Buck et al., 2023), and increasing operational costs (Guo et al., 2023). There is also a non-linear relationship proposed, including a U-shaped (Sarkis et al., 2021; Ha et al., 2022; Peng et al., 2022; Yang Y. et al., 2023) and inverted U-shaped relationships (Dou and Gao, 2022; Li, 2022; Wang et al., 2023d). Individual studies have also investigated the relationship between digitization and different dimensions of greenization, revealing heterogeneity in their impacts, such as He et al. (2023) found that digitization can significantly affect green innovation, but when categorizing green innovation into substantive and strategic green innovation, digital transformation only positively impacts substantive green innovation.

The third aspect focuses on contextual factors that influence the relationship between digitalization and greenization, particularly organizational slack. Scholars have examined the influence of external environmental factors such as environmental regulation (Shen and Wang, 2023), economic development level (Wang C. et al., 2023) and media attention (Li J. et al., 2023), as well as the moderating effect of internal organizational variables such as board characteristics (Chen and Hao, 2022) and internal control (Fan et al., 2023). Only a few studies have considered organizational slack as a contextual factor. Some studies find that slack resources can moderate the impact of digitalization, for example, Zhang K. et al. (2023) found that slack resources can positively moderate the inhibition effect of digital transformation on greenwashing behavior. In contrast, others examine how the direction or degree of influence of organizational or environmental factors on firm greening changes with variations in slack resources. Findings in this area are inconsistent (e.g., Sun and Sun, 2021; Zhang J. et al., 2022; Xiao et al., 2023; Gao and Yang, 2023). However, it should be pointed out that, a few pioneers consider organizational slack as the boundary condition of the relationship between digital transformation and corporate greenization, and find that absorbed, unabsorbed, and potential slack resources positively moderate the impact of artificial intelligence on green total factor productivity (Ying et al., 2023).

Previous research has made significant strides, yet certain gaps remain. Firstly, the concepts of digital transformation and corporate greenization are often treated holistically, lacking a detailed breakdown of their types or dimensions, as well as novel measurement methods based on these dimensions. Many studies default to treating these variables as one-dimensional, focusing solely on revealing the underlying mechanisms. While this approach can contribute new knowledge, it also adds to the complexity of the knowledge system. Secondly, there is a dearth of systematic research on the impacts of different dimensions of digital transformation on various greenization strategies. Existing literature primarily focuses on the influence path, with few studies analyzing the influence of digitization on the dimensions of greenization. The examination of their relationship at the dimension or category level remains incomplete. Lastly, the boundary conditions of digitalization affecting greenization, from the perspective of slack resources, have received limited attention. Although some papers explore the moderating effect of slack resources, there is a lack of comprehensive analysis on how these resources influence the relationship between the various dimensions of the core variable.

To address the aforementioned gaps, this paper aims to investigate the relationship between different dimensions of digital transformation and the process of corporate greenization, taking into account the potential moderating influence of various types of slack resources from a heterogeneity perspective. According to the application of digital technology, digital transformation can be categorized into two dimensions: breadth of digital transformation (BODT) and depth of digital transformation (DODT). BODT refers to the scope of digital technologies and related tools adopted by enterprises in the process of digital transformation, including both "underlying technologies" such as artificial intelligence and blockchain, and "practical applications" that arise from leveraging these underlying technologies in specific businesses or scenarios, such as mobile internet and industrial internet (Feng et al., 2022; Ren et al., 2022). DODT pertains to the degree or intensity of investment in resources (Yang Z. et al., 2023) and attention (Resch and Kock, 2021) that enterprises allocate to adjusting or reconstructing various elements of the organization using these underlying technologies and practical applications. Corporate greenization is the process through which companies innovate in energy conservation, emissions reduction, and resource utilization to achieve a harmonious development of the economy and the environment. Building on research on green innovation performance (Yang et al., 2022), corporate greenization can be further classified into two dimensions: input of corporate greenization (IOCG) and output of corporate greenization (OOCG). IOCG primarily encompasses investments in environmental protection equipment and clean manufacturing technologies, while OOCG refers to the acquisition of green products and the outcomes of green innovation. Slack resources are resources that go beyond the daily operational requirements of a company and can be utilized in the future (Bourgeois and Singh, 1983; Nohria and Gulati, 1996). They are often classified based on their degree of liquidity as absorbed slack resources (ASR) and unabsorbed slack resources (USR) (Singh, 1986). ASR are resources earmarked for specific purposes closely linked to the core business, such as excess production equipment and idle plants. USR, in contrast, encompass resources that lack specific earmarking and are not intrinsically tied to ongoing business operations or strategic planning, like available cash or equivalents. Based on the definitions provided above, this paper utilizes data from listed companies on the Shanghai and Shenzhen stock exchanges from 2011 to 2020 to examine the impact of digital transformation on greening of enterprises. The empirical results indicate that both BODT and DODT have a negative impact on IOCG, while exerting a positive influence on OOCG, with DODT demonstrating a more pronounced impact. Additionally, both ASR and USR weaken the relationship between BODT/DODT and IOCG, while also attenuating the positive impact of BODT/DODT on OOCG, with ASR exhibiting a stronger moderating effect.

Our study has made several contributions. Firstly, we have deconstructed the core variables of digitization and greenization, taking into account the realities of these phenomena, and have developed innovative measurement methods. Previous research has often treated digitalization and greenization as unidimensional variables, with only a limited number of studies exploring their subcategories. In contrast, our study breaks down digitization into breadth and depth, which captures the scope and scale of business changes facilitated by "underlying technologies" and "practical applications." This approach enhances our understanding of the various modes and diversity of digital transformation at a deeper level. Furthermore, we conceptualize greenization in terms of inputs and outputs, which effectively captures the utilization and allocation of green resources, providing a more comprehensive understanding of operational activities and management effectiveness in business greening. Additionally, we measure the breadth and depth based on the categorization and proportion of digital texts, which not only demonstrates the originality of our measurement method but also establishes a foundation for empirical research on digital transformation.

Secondly, we examine the specific effects of different dimensions of digital transformation on corporate greenization strategies from a heterogeneity perspective. While most articles focus on investigating the intrinsic mechanisms through which digitalization influences greenization, only a few scholars have explored this relationship through dimensionalization and categorization. In contrast, we not only explore the direction and intensity of the impact of BODT/DODT on IOCG or OOCG, but also compare the effects of BODT and DODT. This not only provides new insights for academic analysis of how digitalization truly affects greenization but also offers valuable guidance for practitioners seeking to understand this complex relationship.

Thirdly, we uncover the boundary conditions of the impact of digital transformation on green practices within the context of slack resources. While many scholars have analyzed moderating variables, their focus has primarily been on these general external environmental and internal organizational factors. Although some studies have considered slack resources as a boundary condition, they have not thoroughly examined their moderating effects on the relationship between the dimensions of these variables. In contrast, our study integrates the behavioral theory of the firm and principal-agent theory to discuss the impact of organizational slack on the relationship between BODT/DODT and IOCG/OOCG. We also compare the moderating effects of ASR/USR. Our findings demonstrate that slack resources can be seen as “sweet burdens” to a certain extent, providing new evidence on how companies can adjust the relationship between digitization and greenization through resource allocation.

The remainder of this study is organized as follows: Section 2 constructs the theoretical framework and proposes research hypotheses. Section 3 describes the data sources, variable measurements, and empirical models. Section 4 presents the results of hypothesis testing and robustness checks. Section 5 discusses the research findings and policy recommendations.

2 Theoretical framework and research hypotheses

The resource-based theory, the behavioral theory of the firm, and agency theory provide valuable theoretical lenses for understanding the relationship between digital transformation and greenization. The resource-based theory elucidates the process by which firms generate competitive advantage through the utilization of their resources and dynamic capabilities (He et al., 2023). Initially, the resource-based view held dominance, emphasizing the criticality of valuable, scarce, non-imitable, and non-substitutable resources in driving a company’s long-term success (Barney, 1991). However, in light of rapid technological advancements, intense market competition, and evolving governmental regulations, the efficient redistribution of resources by enterprises has emerged as a paramount concern, giving rise to the concept of dynamic capabilities. In contrast to the resource-based view, the theory of dynamic capabilities underscores the significance of firms’ capacity to effectively integrate, develop, and reconfigure resources in response to swiftly changing environments (Teece et al., 1997).

From the perspective of the resource-based theory, digital transformation can potentially impact the greening of businesses by providing them with unique and valuable resources or enhancing their ability to reconfigure resources. The acquisition of resources and the development of capabilities further influence the input or output of corporate greenization (Alzamora-Ruiz et al., 2021; Barroso-Castro et al., 2022). However, the role of digital transformation may vary between IOCG and OOCG. IOCG refers to the financial investment made by enterprises in exploring and developing new greening opportunities, which is within their control. OOCG, on the other hand, represents the final patented knowledge or newly developed product obtained after a lengthy process, which is difficult for enterprises to control and predict (Duran et al., 2016). Therefore, it can be observed that while digital transformation promotes greenization output by expanding resource sets, optimizing business processes, and restructuring business models, it may also significantly increase investment in digital assets, leading to a complex organizational structure and potentially encroaching on green resources. Overall, while digital transformation has a “promoting effect” on OOCG through the acquisition of resources and capabilities, it may also have an “inhibiting effect” on IOCG through the depletion of resources and capabilities.

The behavioral theory of the firm conceptualizes a corporation as a coalition of self-interested groups, and the conflicts arising among these groups influence the decision-making process of the corporation, including pricing, output, and other factors (Cyert and March 1963). According to this perspective, corporations possess multiple and diverse objectives that emerge from negotiations among various self-interested groups. Furthermore, in the pursuit of these objectives, enterprises do not aim to maximize outcomes but rather strive for satisfactory performance. Throughout the pursuit of satisfactory performance, these groups encounter limitations in terms of information availability, time constraints, resource scarcity, managerial expertise, and uncertainties arising from changes in external market conditions and competitors’ behavior. Consequently, corporate decision-making involves a continuous learning process through trial and error, ultimately enhancing the adaptability of the enterprise (Walker, 2016).

According to the behavioral theory of the firm, the presence of slack resources can help mitigate the conflict of interest between the digital transformation group and the green innovation group during the process of digitalization and greenization. To some extent, the existence of slack resources can alter the acceptability of decision-making standards and increase the tolerance for risks associated with these initiatives. It also enables organizations to better cope with uncertainties that arise during the digitalization and greenization process (Thompson, 1967; Galbraith, 1973). Ultimately, slack resources enhance organizational flexibility and may weaken the negative relationship between digital transformation and investments in greening initiatives.

The principal-agent theory considers the firm as a contractual relationship where the principal delegates decision-making authority to the agent to act in their best interests, while compensating the agent for their services (Ross, 1973). In modern corporations, where ownership and control are separated, there exists an information asymmetry between investors and executives (Holmstrom, 1979), and executives are assumed to be rational economic agents (Holmstrom and Tirole, 1989). This gives rise to agency problems when executives act against the interests of investors to pursue their own private gains (Arrow, 1985), such as managers choosing projects with lower risk and lower returns when making investments. According to this theory, slack resources can potentially undermine the efficiency of green innovation (Zhu et al., 2022). Specifically, slack resources may exacerbate the information asymmetry between external investors or owners and corporate executives, providing opportunities for executives to engage in moral hazard behaviors to serve their own interests. They may also expand the discretionary power of executives to a certain extent, ultimately compromising the operational and decision-making efficiency of the enterprise. Therefore, organizational slack not only weakens the negative impact of digital transformation on

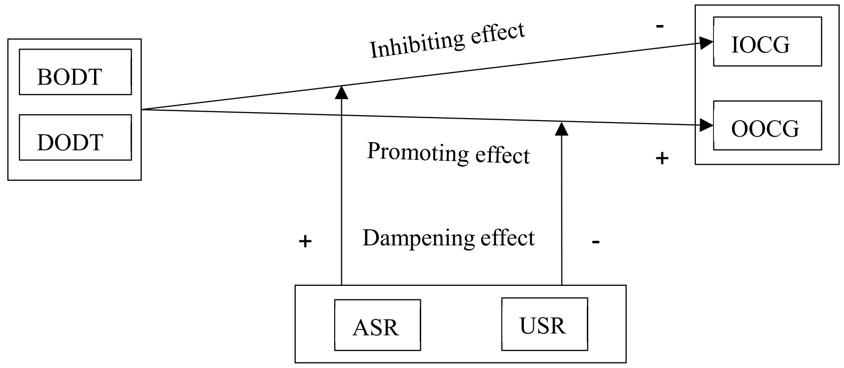

FIGURE 1
Theoretical framework.

IOCG but also hinders the positive relationship between digital transformation and OOCG.

Building upon the aforementioned information, we draw a theoretical framework (Figure 1) that illustrates the relationship among the key variables. Utilizing this framework as a foundation, we put forward a set of hypotheses that will be further expounded upon in the forthcoming chapters.

2.1 Relationship between digital transformation and corporate greenization

2.1.1 BODT/DODT and IOCG

Digital transformation has the potential to overshadow a company's commitment to environmental sustainability. The process of digitalization often requires significant investments in assets, personnel, materials, and funds. Similarly, the implementation of green strategies within a company, aimed at achieving energy conservation, emission reduction, and pollution prevention (Gee and McMeekin, 2011; García-Pozo et al., 2015), demands investments in new technologies, knowledge, and innovative ideas. As a result, there may be a conflict between utilizing digital resources and investing in green initiatives. Given that the benefits of green investments often take a significant amount of time to materialize (Chen and Ma, 2021), combined with the performance and cash flow challenges associated with green development, companies may prioritize limited innovation resources towards digitalization rather than greenization. Unfortunately, this can lead to a shortage of green resources necessary for driving sustainable transformations.

Digital transformation has the potential to weaken a firm's ability to discover, integrate, and utilize resources. While digital technology can generate and unlock value for businesses, it can also result in a significant increase in external transaction costs and internal organizational costs (Guo et al., 2023), ultimately hindering the improvement of resource search capabilities and damaging the identification of firm resources. Furthermore, digital transformation may negatively impact the ability to adjust or reconfigure resources. Although companies can monitor and analyze real-time data on resource procurement channels, price fluctuations, and supply and demand conditions through the use of data analysis models and computational algorithms, the adoption of new technologies may lead to a new monopoly where entities with higher digital power in the innovation ecosystem may more easily acquire and integrate resources (Li et al., 2016), ultimately resulting in unfair resource allocation. Similarly, when digital transformation is too broad and too fast, existing organizational capabilities may not meet the requirements (Gebauer et al., 2020), leading to underutilization or even waste of resources. In such situations, enterprises may be reluctant to invest in green resources considering the externality and public goods attribute of green activities (Chen et al., 2022). Therefore, we propose the following hypothesis:

H1: Both BODT and DODT are negatively correlated with IOCG overall.

2.1.2 BODT/DODT and OOCG

Digital transformation can bring the green resources needed for green transformation. From a resource discovery standpoint, digital transformation facilitates enterprises in establishing and expanding their value networks, and a large amount of information and data are constantly exchanged between enterprises and among enterprises' internal entities, reducing their reliance on complementary green resources to a large extent (He et al., 2023). Simultaneously, digitalization promotes the upgrading of enterprise value chains and optimization of industrial structures (Li X. et al., 2023; Zhang W. et al., 2023; Wang J. et al., 2023), creating conditions for firms to obtain green resources from a wider range of channels. In terms of resource transfer, the use of digital and intelligent technologies helps firms build digital supply chains with partners, creating digital platforms among internal entities, which not only alleviates information asymmetry but also greatly reduces the cost of knowledge sharing (Zhang Q. et al., 2022). Regarding resource absorption, based on new technologies such as artificial intelligence and big data, firms can extract valuable information from large-scale, real-time interactive data, strengthening risk control in the process of resource utilization. Additionally, digitization helps enterprises to update innovative resources in real-time or restructure the relationship architecture between resources. According to the resource-based theory, the discovery, transfer, and absorption of green resources play a powerful role in promoting enterprises to achieve green innovation goals.

Digital transformation may also enhance green innovation capabilities and reduce the costs of green product development (Yang et al., 2022). On one hand, digital transformation encourages enterprises to reduce the production cost of green products through routine updates, resource bricolage, and synergy effects. Routine update is an essential process involved in the digitalization of enterprises, which entails modifying and revamping existing procedures and patterns. The combination of emerging technologies and production processes prompts companies to update or adopt new management models when offering products to customers. This change in conventions creates favorable conditions for firms to engage in green innovation, such as “source reduction” and “end-of-pipe cleaning” (Liu X. et al., 2023), ultimately accelerating the speed of green transformation. Resource bricolage refers to the strategic identification and integration of resources by utilizing modules and interface rules offered by digital platforms, helping to alleviate institutional and resource constraints. Compared to acquiring resources from external networks or creating unique resources, embedding in digital platforms ensures resource specificity and reduces acquisition costs. Synergy effects occur when firms and other entities cooperate and gain benefits that exceed what they would achieve as independent units. Within an ecosystem, network effects facilitate the sharing of product design inspiration between firms and other entities, driving iterative improvements based on market response and ultimately reducing the cost of acquiring new ideas.

On the other hand, digital transformation has the potential to enhance firms’ capabilities for green innovation through the renewal of their knowledge base, iteration of intellectual capital, and innovation in their business models. Knowledge base renewal involves the reconstruction and updating of skills, knowledge, tools, and other resources within a firm, facilitated by digital technologies, to meet the specific needs and requirements of the firm. Throughout the process of digital transformation, enterprises can acquire new skills for task completion, learn novel methods of value creation, and even generate entirely new knowledge. According to the resource-based theory, the updating of the knowledge base is expected to significantly expand enterprises’ capacity for green innovation, ultimately enabling the realization of green transformation. Intellectual capital iteration refers to the evolution of human capital, organizational capital, and relational capital driven by the application of digital technologies. Serving as a powerful driver of the synergistic transformation of various elements within firms, digital change and innovation are accompanied by continuous investments in intellectual capital (Li J. et al., 2023). The investment in intellectual capital will inevitably enhance the innovation capacity of green processes and products, thereby exerting a positive influence on the greening of enterprises. Business model innovation entails the adjustment of the value creation process based on changes in business logic, supported by digital technology. As digital transformation continues to advance, firms have the opportunity to innovate their business models based on customer feedback, surpassing previous experiences and limited rationality. Aligned with business model innovation, the capacity for green innovation is strengthened, ultimately overcoming barriers to the transformation into environmentally friendly enterprises. Therefore, we propose the following hypothesis:

H2: Both BODT and DODT are positively correlated with OOCG overall.

2.1.3 Differences in the effects of BODT and DODT

BODT and DODT may have distinct influences on the greening of enterprises. BODT, which stands for breadth of digital asset deployment (Ye et al., 2022), refers to the number of technologies and tools adopted by enterprises in their digitization efforts (Yang Z. et al., 2023). On the other hand, DODT, or depth of digital asset deployment (Ye et al., 2022), reflects the level of attention and resource investment dedicated to digital asset deployment. While BODT indicates the adoption of specific digital technologies, DODT signifies the extent to which the potential of these technologies is fully utilized (Blichfeldt and Faullant, 2021). When a technology is fully leveraged, it demonstrates a firm’s solid foundation in knowledge and expertise, acting as a critical catalyst for driving innovation and progress within the firm (Katila and Ahuja, 2002). Regarding the relationship between digitalization and greenization, a broader BODT enables firms to explore more combination innovations in green processes and products. Conversely, a deeper DODT suggests that firms are more familiar with new technologies and possess a stronger knowledge base tailored to these technologies (Blichfeldt and Faullant, 2021), increasing the likelihood of implementing green innovation strategies. Furthermore, some studies have compared the effects of BODT and DODT, finding that DODT has a stronger impact. For instance, in the context of the relationship between digital asset deployment and supply chain agility, the depth of digital asset deployment has a significant positive effect on supply chain agility, rather than the breadth of deployment (Ye et al., 2022). Based on the above, we propose the following hypothesis:

H3: Compared with BODT, the relationship between DODT and IOCG/OOCG is stronger.

2.2 The moderating role of slack resources

2.2.1 The moderating role of slack resources in the relationship between BODT/DODT and IOCG

The presence of slack resources can help mitigate conflicts and tensions between advocates of digital transformation and proponents of green investment. As self-interested individuals with different priorities, the concerns of digital transformation advocates and green investment supporters may not align, leading to competition for limited corporate innovation resources. In situations where resources are scarce, these stakeholders may engage in bargaining and political struggles, potentially diverting management decisions away from strategic goals and towards serving their own interests (Moch et al., 1977). However, when an organization has abundant slack resources, the needs and demands of both digital transformation initiatives and green investment proponents can be more adequately met. With sufficient resources available, the intensity of their competition for resources is reduced. This, in turn, weakens the negative impact of digital transformation on the implementation of green initiatives, as both parties can find a more harmonious balance between their respective goals.

The presence of surplus resources can influence an organization's inclination towards adopting digital and green solutions, as well as the level of commitment exhibited by managers towards digital and green risks. On one hand, when considering performance objectives, digital transformation primarily serves short-term performance goals, whereas greening initiatives aim to achieve harmonious development between the organization and the environment. In situations where resource limitations are a concern, enterprises may prioritize enhancing short-term performance and hesitate to allocate necessary resources towards greening efforts. Conversely, in resource-abundant scenarios, enterprises are more inclined to invest substantial funds, even if greening initiatives do not yield immediate results. This shift occurs because the selection criteria for enterprise transformation plans transition from "maximization" to "satisfactory" (Simon, 1967). On the other hand, both digitalization and greening initiatives entail significant risks for organizations. When faced with the choice between the two, companies may prioritize digitalization over greening. However, when enterprises possess surplus resources, they need not excessively worry about the high risks associated with innovation and change (Baird and Thomas, 1985; Singh, 1986). This allows them to consider both digital innovation and green development, rather than neglecting one in favor of the other.

Slack resources help enterprises to reduce resource crowding and misappropriation brought by digital transformation while advancing digitalization in an orderly manner under uncertainty. By acting as a "buffer" for both the organization and the environment, organizational slack create a margin of improvement that allows the enterprise to navigate environmental changes more effectively (Levinthal and March 1981). This, in turn, enables the enterprise to gradually or cautiously implement digital transformation initiatives. Consequently, the core operations of the enterprise experience minimal disruption (Thompson, 1967), and the overall shock caused by the transformation is mitigated, thereby reducing the adverse effects of digital transformation on greening efforts. Based on these observations, the hypothesis is proposed:

H4: Both USR and ASR play a negative moderating role in the impact of BODT/DODT on IOCG, that is, the more ASR and USR, the weaker the negative correlation between BODT/DODT and IOCG.

2.2.2 The moderating role of slack resources in the relationship between BODT/DODT and OOCG

While slack resources can provide certain benefits, it is important to acknowledge that they can also exacerbate information asymmetry and create conditions that encourage executives to engage in moral hazard behaviors to serve their own interests. As a buffer, redundant resources introduce a barrier between external investors and executives, making it more challenging for investors to observe and predict the utilization of green resources (Zhu et al., 2022). Particularly in situations where there is an expectation gap or organizational decline, idle resources can transmit ambiguous or even misleading signals to stakeholders, reducing the regulatory pressure faced by executives and weakening their sense of urgency in implementing corporate strategies (Wang et al., 2016). Furthermore, these surplus resources enable executives to allocate resources towards the development of innovative products in a manner that prioritizes their personal interests, without adequately considering the overall economic interests of the company (Child, 1972). As agents operating under the separation of ownership and control, executives are motivated to pursue personal goals such as power and prestige. In the presence of slack resources, they may become overly confident or excessively optimistic, evading corporate responsibilities related to environmental protection and sustainable development (John et al., 2008). They may disregard the long-term value that can be derived from the enterprise's green innovation (Tan and Peng, 2003), leading to inefficient resource utilization, wastage, and ultimately, a negative impact on the enterprise's capacity to produce green patents and green products (Arena et al., 2018).

In addition to exacerbating information asymmetry and moral hazard, slack resources also increase the discretion of executives, resulting in higher corporate governance costs. On one hand, while these resources can provide protection against external environmental impacts (Liu et al., 2014), they also enable top management teams (TMTs) to exercise greater decision-making autonomy. When executives harness innovative resources, they often rely on their instincts rather than engaging in trial-and-error to identify the most effective resource utilization strategies. Consequently, in the context of digital transformation, the presence of slack resources may lead managers to over-diversify their resource utilization practices (Salge and Vera, 2013). This not only diminishes their ability to effectively search for, integrate, and utilize resources but also increases the management costs associated with resource transfer, allocation, and related procedures. As a result, the positive impact of digital transformation on OOCG is weakened. On the other hand, the existence of slack resources requires enterprises to invest significant time and energy in transforming these resources into products or services, which also increases the costs for stakeholders to supervise the utilization of these resources to a certain extent. When the scope of resource integration extends beyond firm boundaries or becomes excessively large, the time and cost associated with resource selection, integration, and utilization escalate. This may even result in diseconomies of scale and scope in technology application (Breschi et al., 2003). Moreover, when enterprises possess excess resources, executives gain more opportunities to prioritize their own "favored projects," potentially impeding resource owners or providers from effectively monitoring executive behavior due to false resource utilization (Li-Ying et al., 2014). Consequently, agency costs rise, significantly diminishing the role of digital transformation in promoting environmentally sustainable output. Therefore, we propose the following hypothesis:

H5: Both USR and ASR play a negative moderating role in the impact of BODT/DODT on OOCG, that is, the more ASR and USR, the weaker the positive correlation between BODT/DODT and OOCG.

2.2.3 Differences in the roles of ASR and USR

Both ASR and USR have an impact on the relationship between digitalization and greenization, but their effects may differ. ASR are resources that exist for a specific business or process during product production and are difficult to use for other purposes once they are applied to the production process of a product (Sharfman et al., 1988). In contrast, USR are not limited to a specific technical field, business operations, or production management (Tan and Peng, 2003) and can be used for more innovative activities. In the context of digitalization influencing green development, ASR has a higher degree of specificity, greater coordination cost, and is more likely to generate resource stickiness and structural rigidity (Greve, 2003). When resources are excessively invested in business operations, it is more likely to produce a "siphon effect," which can lead to enterprises falling into a dilemma of resource allocation. Therefore, the moderating role of ASR may be greater than that of USR. On the other hand, ASR has a lower conversion efficiency than USR, as it is less flexible and liquid, and its utilization and transformation also require higher costs. When a firm faces organizational inertia (Henderson and Clark, 1990), inadequate management incentive systems, or internal control failures (Hitt et al., 1991), ASR may exhibit a higher degree of inefficient allocation. Thus, compared to USR, ASR has a stronger moderating effect. Based on these considerations, we propose the following hypothesis:

H6: Compared with USR, ASR has a stronger moderating effect.

3 Research design

3.1 Sample and data

To investigate the association between BODT/DODT and IOCG/OOCG, as well as the moderating influence of ASR/USR, we utilize data from companies listed on the Shanghai and Shenzhen stock exchanges in China spanning the period from 2011 to 2020. The choice of 2011 as the starting year aims to mitigate the potential influence of executive discretion on disclosure practices. In 2010, the Ministry of Environmental Protection issued the "Guidelines for Environmental Information Disclosure of Listed Companies," mandating that companies operating in heavily polluting industries commence regular environmental information disclosure and publication of environmental reports from 2011 onwards. After excluding observations with missing values, our final dataset comprises 26,902 observations. To mitigate the impact of outliers, we winsorize the tails of the continuous variables by 1 percent. Data collection involves manual compilation from company annual reports or retrieval from the CSMAR database.

3.2 Measurements of variables

3.2.1 Dependent variables

Corporate greenization is characterized by a dynamic and evolving process. In this study, we adopt the classification proposed by Qi et al. (2023) and categorize it into two dimensions: IOCG and OOCG. IOCG, as defined by Huang and Lei (2021), includes the investments and expenditures made by enterprises in environmental protection equipment, cleaning technology, and pollution control measures. To address the inherent right-skewness in green investment data (Fan et al., 2023), we apply a natural logarithm transformation after adding 1 to the total green investment of listed companies. Regarding OOCG, we adopt the analytical perspective put forth by He et al. (2023) and Feng et al. (2022), which utilizes the number of green patent applications as a proxy measure. The choice of using the number of green patent applications is motivated by its intuitive reflection of the efficiency of green resource utilization by enterprises. Furthermore, it is considered more stable, reliable, and timely compared to patent grant data (Li and Shen, 2021). Specifically, we measure OOCG by considering both the number of green patents applied for by individual companies and those applied for jointly with other companies.

3.2.2 Independent variables

Previous literature has employed three distinct methodologies to measure digital transformation. The first approach involves using a binary variable to indicate whether an enterprise has undertaken digital transformation (Wang C. et al., 2023). However, this method has been criticized for its limited ability to comprehensively capture the extent of organizational transformation (Fan et al., 2023). The second method involves selecting a restricted set of financial or non-financial indicators (Wen et al., 2021), which may not fully reflect the multi-faceted nature of digital transformation. The third method involves administering questionnaires to subjects, but this approach has limitations in terms of objectivity.

In line with the methodology proposed by Li J. et al. (2023) and Zhang G. et al. (2023), this study employs a textual analysis of annual reports from publicly traded companies to evaluate the content and extent of digital transformation. The procedural sequence is as follows: Firstly, a digital transformation text database is created. To ensure the comprehensiveness, accuracy, and authority of the texts, we utilized a compilation of texts from Chinese and English literature, as previously explored by Wu et al. (2021) and Ren et al. (2022). These articles encompassed various sources of text, including policy documents, research reports, academic papers, and corporate annual reports. Notably, Wu et al. (2021) extracted text from sources such as the "Special Action Plan for Digital Enablement of SMEs", the "2020 Digital Trends", and the government work report. Subsequently, pairwise comparisons were conducted on the collected texts, resulting in the identification of 120 non-duplicate keywords associated with digital transformation. To illustrate the interrelationships among these keywords, we categorized them into two groups: "underlying technology" and "practical application." The "underlying technology" category encompasses texts related to four key technologies, namely, artificial intelligence, big data, cloud computing, and blockchain. On the other hand, the "practical application" category includes texts describing new tools, patterns, or phenomena arising from the integration of these technologies with various business or scenario contexts. In summary, the aforementioned five types of keywords, totaling 120, constitute the digital transformation text database. Table 1 presents the keywords associated with digital transformation.

Secondly, the annual reports of publicly traded companies were manually collected. Annual reports serve as authoritative documents disclosed by listed companies, providing insights into their development direction and strategic decisions (Donovan et al., 2021). Therefore, we utilized these reports as a foundation for

TABLE 1 The keywords of digital transformation.

Dimension	Category	Key word
Underlying technology	Artificial intelligence	artificial intelligence; business intelligence; image understanding; investment decision aid; intelligent data analysis; intelligent robot; machine learning; deep learning; semantic search; biometrics; face recognition; speech recognition; authentication; autonomous driving; natural language processing
	Big data	big data; data mining; text mining; data visualization; heterogeneous data; credit investigation; augmented reality; mixed reality; virtual reality; imaging; ICT
	Cloud computing	cloud computing; stream computing; graph computing; in-memory computing; multi-party security computing; brain-like computing; green computing; cognitive computing; converged architecture; 100 million-level concurrencies; EB-class storage; Internet of Things; information physical systems; 10 billion-level concurrencies; supercomputer; computing science; cloud platform; edge computing
	Blockchain	blockchain; distributed computing; differential privacy technology; digital currency; smart financial contract
Practical application		mobile internet; industrial internet; Bailian network medical; E-commerce; mobile payment; third party payment; NFC payment; intelligent energy; B2B; B2C; C2B; C2C; O2O; Network connection; smart wear; smart agriculture; intelligent transportation; intelligent medical; intelligent customer service; smart home; intelligent investment advisor; intelligent cultural tourism; intelligent environmental protection; intelligent power grid; intelligent marketing; digital marketing; unmanned retail; internet finance; digital finance; Fintech; financial technology; quantitative finance; open banking; new energy digitalization; intelligent new energy; intelligent new energy system; intelligent new energy management; digital new energy; intelligent emergency; intelligent operation and maintenance; Digital interconnection; digital ecology; digital process; digital business; interactive power grid; digital power grid; intelligent hydropower; hydropower digitization; intelligent battery; intelligent wind power; digital wind power; digital offshore wind power; new energy information; digital wind farm; intelligent microgrid; intelligent photovoltaic; digital photovoltaic; photovoltaic cloud platform; intelligent hydrogen; intelligent light energy; intelligent solar energy; virtual power plant; intelligent oil and gas pipeline; intelligent nuclear energy; intelligent power plant; intelligent power equipment; digital enablement; digital new energy industry; digital new energy monitoring; digital management; intelligent new energy infrastructure

assessing the digital transformation of listed companies. Initially, we downloaded the annual reports from various platforms (e.g., eastmoney.com) and then cross-referenced them with the stock codes in the CSMAR database to identify any missing reports. Subsequently, we conducted a thorough search for the corresponding annual reports of the companies with missing reports, supplementing our dataset accordingly.

Thirdly, we employed the Jieba function in Python for word segmentation. Utilizing a language model, we identified text sections within the company's annual reports that were relevant to digital transformation. Subsequently, we performed segmentation on the identified text, eliminating insignificant modal particles, conjunctions, and duplicate content.

Finally, the segmented text is compared against the digital transformation text database, and the corresponding statistical results are utilized to measure BODT and DODT. In measuring BODT, if the segmented company annual report text does not contain any digital transformation keywords, a value of 0 is assigned. If there is one digital keyword present, a value of 1 is assigned. Similarly, if there are two digital keywords, a value of 2 is assigned, and so on. In other words, BODT is determined by the number of digital transformation texts disclosed within a company's annual report.

Yang Z. et al. (2023) utilized the summation of digital technology-related phrases divided by the number of digital technology types implemented by enterprises to measure DODT. They posited that this approach identified the average effort of enterprises in each digital technology. However, this method solely reflects the degree of emphasis and resource allocation of a single enterprise towards digitalization, without considering the overall impact of digital transformation and potential spillover effects. To achieve a more accurate and comprehensive measurement, we propose an enhancement to Yang Z. et al. (2023)'s method by employing the following formula:

$$DODT_{i,t} = \frac{n_{i,t}}{\sum n_{i,t}} \quad (1)$$

In formula 1, $n_{i,t}$ is the number of digital transformation texts disclosed by listed company i in its annual report for year t; $\sum n_{i,t}$ is the sum of the digital transformation texts disclosed by all listed companies in their annual reports in year t.

3.2.3 Moderator variable

Based on theoretical analysis, we introduce slack resources as moderating variables, specifically USR and ASR. Following the approach of Iyer and Miller (2008), Peng et al. (2010) and Wu and Hu (2020), we employ the quick ratio to quantify USR. The quick ratio is calculated as the disparity between current assets and inventories divided by current liabilities. As for ASR, it is assessed by determining the ratio of the total management expenses and sales expenses to the operating revenue.

3.2.4 Control variables

To control for various factors that may influence enterprise greenization, we consider their own attributes, financial performance, and governance arrangements, as outlined by (Wang C. et al., 2023). The own attributes we examine are age (Age) and size (Size). Age is included to control age-related effects (Czarnitzki and Hottenrott, 2011), while size is considered to address the scale effect (Xiang et al., 2022a). Regarding financial performance, we incorporate the following variables: leverage ratio (Lev), return on assets (Roa), cashflow (Cashflow), growth rate (Growth), sales revenue to operating expenses ratio (Mpower). These variables have been found to have some influence on corporate environmental performance (Xue et al., 2022; Li

TABLE 2 Definitions and measurements of main variables.

Variable	Measurement
IOCG	The natural logarithm of one plus the environmental protection expenditure of corporate
OOCG	The number of green patents independently applied by the corporate and jointly applied with other corporates
BODT	The types of digital text in corporate annual reports
DODT	The number of digital text in corporate annual reports/the sum number of digital text of all corporate annual reports in the same year
ASR	(Administrative expenses + selling expenses)/operating revenue
USR	(Liquid assets-inventory)/liquid liabilities
Age	The number of years since the listing date
Size	The natural logarithm of annual total assets
Lev	The annual total liabilities/annual total assets
Roa	Net profit/annual total assets
Cashflow	Current net cash flow/annual total assets
Growth	(Operating income in year t- operating income in year t-1)/operating income in year t-1
Dual	Same person equals to 1, otherwise 0
Board	The natural logarithm of the number of directors
Indep	The number of independent directors/the number of directors
Top1	Shareholding ratio of the largest shareholder
Soe	State owned equals to 1, otherwise 0
Mpower	Ln (selling income/operating expenses)

J. et al., 2023). In terms of corporate governance, we adopt the recommendations of Choi et al. (2020) and Feng et al. (2022). Specifically, we include integration of two functions (Dual), number of directors (Board), proportion of independent directors (Indep) and proportion of the largest shareholder (Top1). Additionally, we consider whether the enterprise is state-owned or not (Soe). Please refer to Table 2 for a detailed explanation and measurement of each variable.

3.3 Empirical model

Based on existing literature (e.g., He et al., 2023), the following multiple linear regression model (Eqs 2, 3) was established:

$$IOCG\,(OOCG)_{i,t} = \alpha_0 + \alpha_1 BODT\,(DODT)_{i,t} + \sum \alpha_k Controls_{i,t} + \varepsilon_{i,t} \quad (2)$$

$$IOCG\,(OOCG)_{i,t} = \delta_0 + \delta_1 BODT\,(DODT)_{i,t} + \delta_2 ASR\,(USR)_{i,t} + \delta_3 BODT\,(DODT)_{i,t} {}^{*} ASR\,(USR)_{i,t} + \sum \delta_k Controls_{i,t} + \varepsilon_{i,t} \quad (3)$$

Equation 2 tests the direct effect of BODT or DODT on the greening of an enterprise. Equation 3 investigates the influence of the interaction of digital transformation and slack resources on corporate greenization. To account for industry sector and year-specific trends in greenization input or output, we incorporate industry and year fixed effects into our regression models.

4 Empirical results

4.1 Descriptive statistics

Table 3 presents the descriptive statistics for the key variables. In this table, the IOCG variable exhibits a high mean value and a large variance, suggesting that the sampled enterprises have made substantial investments in environmental protection equipment and green processes, with significant variations in investment levels. Conversely, the OOCG variable displays a small mean value but a large variance, indicating that the sampled companies have relatively few green patent applications, yet the number of patent applications differs significantly across companies. The mean and variance of BODT are calculated as 2.3894 and 3.2313, respectively, while the corresponding values for DODT are 0.0002 and 0.0006, respectively. These results suggest that the sampled companies employ diverse digital technologies, but their overall level of digital transformation remains relatively low. Regarding slack resources, both the mean and variance of ASR are smaller than those of USR, implying that the sampled enterprises tend to allocate resources with higher liquidity.

TABLE 3 Descriptive statistics.

Variables	Obs	Mean	Std. Dev.	Min	P50	Max
IOCG	26,902	5.2032	7.6339	0.0000	0.0000	20.7047
OOCG	26,902	1.9262	6.2167	0.0000	0.0000	45.0000
BODT	26,902	2.3894	3.2313	0.0000	1.0000	15.0000
DODT	26,902	0.0002	0.0006	0.0000	0.0000	0.0041
ASR	26,902	0.1730	0.1431	0.0153	0.1326	0.8107
USR	26,902	1.8991	2.2305	0.1619	1.1902	14.3952
Age	26,902	2.8077	0.3651	1.6094	2.8903	3.4657
Size	26,902	22.1607	1.2995	19.5914	21.9927	26.1467
Lev	26,902	0.4344	0.2133	0.0539	0.4246	0.9553
Roa	26,902	0.0367	0.0691	−0.2890	0.0367	0.2178
Cashflow	26,902	0.0437	0.0709	−0.1842	0.0436	0.2417
Growth	26,902	0.1020	0.3238	−0.9893	0.0928	1.4697
Dual	26,902	0.2751	0.4465	0.0000	0.0000	1.0000
Board	26,902	2.1278	0.1982	1.6094	2.1972	2.7080
Indep	26,902	0.3754	0.0533	0.3333	0.3571	0.5714
Top1	26,902	0.3406	0.1477	0.0873	0.3181	0.7409
Soe	26,902	0.3441	0.4751	0.0000	0.0000	1.0000
Mpower	26,902	0.3772	0.3137	−0.0229	0.2928	1.7390

TABLE 4 Pearson correlation.

Variables	IOCG	OOCG	BODT	DODT	ASR	USR
IOCG	1.0000					
OOCG	0.0871***	1.0000				
BODT	−0.1797***	0.1222***	1.0000			
DODT	−0.1612***	0.0708***	0.6219***	1.0000		
ASR	−0.1747***	−0.0670***	0.0900***	0.1440***	1.0000	
USR	−0.1483***	−0.0505***	0.0467***	0.1106***	0.2374***	1.0000

Note: ***, ** and * represent 1%, 5% and 10% significance levels, respectively.

4.2 Correlation analysis

Table 4 presents the Pearson correlation coefficients among the key variables. The results show that both BODT and DODT are negatively correlated with IOCG. On the contrary, there is a clear positive correlation between them and OOCG. These findings suggest that digital transformation does not necessarily lead to improved environmental performance in enterprises. Regarding the role of slack resources, both ASR and USR exhibit significant negative correlations with corporate greenization, while displaying significant positive correlations with digital transformation. This indicates that these resources have a positive impact on the digitalization of enterprises. Additionally, the absolute values of the correlation coefficients for each variable are generally small, suggesting the absence of multicollinearity issues.

4.3 Empirical results

4.3.1 Effects of digital transformation

To examine the impact of digital transformation on the greening of firms, we employ ordinary least squares (OLS) estimation. The regression model controls for various firm and industry characteristics that may affect greenization. Additionally, year and industry dummy variables are included to account for potential time and industry-specific effects. The results of the

TABLE 5 Basic regression.

Variables	IOCG	IOCG	OOCG	OOCG
BODT	−0.2910***		0.2193***	
	(0.0168)		(0.0142)	
DODT		−884.1720***		660.1011***
		(76.8119)		(64.7859)
Age	0.2908**	0.3041**	−0.4932***	−0.5035***
	(0.1355)	(0.1359)	(0.1143)	(0.1146)
Size	1.2908***	1.2322***	1.3158***	1.3603***
	(0.0428)	(0.0427)	(0.0361)	(0.0360)
Lev	−0.6106**	−0.5948**	0.5136**	0.5246**
	(0.2653)	(0.2663)	(0.2239)	(0.2246)
Roa	−1.6451**	−1.5467**	4.9229***	4.8486***
	(0.7780)	(0.7803)	(0.6565)	(0.6581)
Cashflow	2.6031***	2.6816***	1.1464**	1.0849**
	(0.6596)	(0.6617)	(0.5566)	(0.5581)
Growth	0.0202	0.0295	−0.5446***	−0.5510***
	(0.1402)	(0.1407)	(0.1183)	(0.1187)
Dual	−0.4357***	−0.4856***	0.1537*	0.1915*
	(0.0993)	(0.0995)	(0.0838)	(0.0840)
Board	−0.0596	−0.0395	0.5980***	0.5831**
	(0.2723)	(0.2731)	(0.2298)	(0.2303)
Indep	−2.3158**	−2.4397**	1.1329	1.2283
	(0.9530)	(0.9560)	(0.8043)	(0.8063)
Top1	0.3530	0.4112***	−0.7146***	−0.7595***
	(0.0472)	(0.3083)	(0.2593)	(0.2600)
Soe	0.7622***	0.8380***	−0.0205	−0.0781
	(0.1064)	(0.1065)	(0.0898)	(0.0899)
Mpower	−2.5614***	−2.5457***	−0.4174***	−0.4287***
	(0.1581)	(0.1587)	(0.1334)	(0.1339)
_cons	−21.6121***	−20.1555***	−28.4354***	−29.5393***
	(1.1728)	(1.1711)	(0.9898)	(0.9877)
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	26,902	26,902	26,902	26,902
Adj-R^2	0.1943	0.1893	0.1347	0.1304

Note: ***, ** and* represent 1%, 5% and 10% significance levels, respectively.

basic regression analysis are presented in Table 5. In columns 1 and 2, the coefficient of the digital transformation dimension on IOCG is found to be negative and statistically significant at the 1% level. These findings support hypothesis H1, suggesting that digital transformation indeed utilizes green resources, thereby weakening green innovation and creating a "crowding out effect" on green investment. This result aligns with previous studies, such as Truby (2018) who argued that the energy-saving effect of digital transformation is limited. In fact, the application of digital communication technology can even lead to a rebound effect, resulting in increased energy consumption.

In columns 3 and 4, the coefficient of the digital transformation dimension on OOCG is positive and statistically significant at the 1% level, supporting hypothesis H2. These results suggest that while digital transformation may crowd out IOCG, it can also enrich green resources, enhance green technology innovation, and ultimately lead to green innovation outcomes for enterprises. These findings are consistent with previous studies, such as He et al. (2023), Feng et al. (2022), and Zhang G. et al. (2023).

The coefficient of BODT on IOCG is −0.2910, while the coefficient of DODT is −884.1720. Similarly, the coefficient of BODT on OOCG is 0.2193, while the coefficient of DODT is 660.1011. These results indicate that both BODT and DODT have a consistent direction of influence on enterprise greening. However, the absolute value of the DODT coefficient is significantly larger than that of the BODT coefficient, suggesting that DODT is a more powerful driver of enterprise greening. This finding supports hypothesis H3. Similar results have been found in previous studies. For instance, Khayer et al. (2023) analyzed the relationship between cloud computing deployment and enterprise performance and found that the coefficient of cloud computing assimilation depth is greater than the breadth.

4.3.2 Roles of slack resources

Table 6 presents the moderating effect of slack resources on the relationship between digital transformation and IOCG. In columns 1 to 4, the coefficients of BODT*ASR, BODT*USR, DODT*ASR and DODT*USR are all positive and statistically significant at the 1% level. This indicates that the presence of more slack resources weakens the impact of digital transformation on IOCG, thereby confirming hypothesis H4. These findings suggest that slack resources can help mitigate internal stakeholder conflicts, influence the risk attitudes of enterprises, act as a "buffer" between the environment and enterprises, and weaken the resource preemption effect of digital transformation.

Table 7 presents the moderating effect of slack resources on the relationship between digital transformation and OOCG. In columns 1 to 4, the coefficients for BODT * ASR, BODT * USR, DODT * ASR, and DODT * USR are negative and statistically significant at the 1% level. This indicates that as slack resources increase, the impact of digital transformation on OOCG is reduced, thus confirming hypothesis H5. The results suggest that an increase in slack resources can enhance managerial discretion, induce higher governance costs, and ultimately weaken the positive effect of digital transformation on OOCG. This finding contrasts with some existing literature that emphasizes the strengthening effect of slack resources on the relationship between digitization and greenization (e.g., Ying et al., 2023).

From a comparative perspective, in Table 6, the coefficient of BODT*ASR is significantly larger than that of BODT*USR, and the coefficient of DODT*ASR is also significantly larger than that of DODT*USR. Similarly, in Table 7, the coefficient of the interaction term between digital transformation and ASR is much larger than

TABLE 6 Moderating regression (IOCG).

Variables	IOCG	IOCG	IOCG	IOCG
BODT	−0.3852***	−0.3755***		
	(0.0238)	(0.0210)		
DODT			−1570.442***	−1304.5970***
			(115.7421)	(96.5874)
ASR	−5.0691***		−4.9396***	
	(0.4908)		(0.4680)	
USR		−0.2376***		−0.2129***
		(0.0279)		(0.0267)
BODT*ASR	0.5655***			
	(0.0938)			
BODT*USR		0.0426***		
		(0.0065)		
DODT*ASR			3239.9500***	
			(381.3209)	
DODT*USR				162.6690***
				(22.5544)
Age	0.3499**	0.2761**	0.3746***	0.3002**
	(0.1353)	(0.1353)	(0.1357)	(0.1357)
Size	1.2142***	1.2942***	1.1520***	1.2285***
	(0.0436)	(0.0428)	(0.0434)	(0.0427)
Lev	0.6358**	−0.3385**	0.6576**	−0.4168
	(0.2649)	(0.3080)	(0.2657)	(0.3092)
Roa	−3.4879***	−1.7136**	−3.5394***	−1.4903*
	(0.8211)	(0.7769)	(0.8211)	(0.7794)
Cashflow	1.8853***	2.4019***	1.9043***	2.4253***
	(0.6619)	(0.6595)	(0.6636)	(0.6617)
Growth	−0.2120	−0.0189	−0.2137	−0.0042
	(0.1425)	(0.1401)	(0.1430)	(0.1407)
Dual	−0.4502***	−0.4289***	−0.4900***	−0.4786***
	(0.0991)	(0.0992)	(0.0993)	(0.0994)
Board	−0.0177	−0.0640	0.0165	−0.0475
	(0.2718)	(0.2719)	(0.2725)	(0.2727)
Indep	−2.2356**	−2.3062**	−2.3167**	−2.4049**
	(0.9516)	(0.9516)	(0.9537)	(0.9545)
Top1	0.2317	0.3961	0.2691	0.4479
	(0.3070)	(0.3069)	(0.3077)	(0.3079)
Soe	0.7424***	0.7247***	0.8150***	0.8234***
	(0.1062)	(0.1064)	(0.1063)	(0.1064)
Mpower	−1.4444***	−2.4678***	−1.4160***	−2.4645***
	(0.2112)	(0.1597)	(0.2114)	(0.1602)
_cons	−19.6031***	−20.7878***	−18.1793***	−19.2782***
	(1.1877)	(1.1798)	(1.1844)	(1.1784)
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	26,902	26,902	26,902	26,902
Adj-R^2	0.1975	0.1966	0.1937	0.1918

(Continued in next column)

TABLE 6 (*Continued*) Moderating regression (IOCG).

Note: ***, ** and, * represent 1%, 5% and 10% significance levels, respectively.

that between digital transformation and USR. These results indicate that ASR has a stronger effect on the relationship between digitization and greenization compared to USR, thus confirming hypothesis H6.

4.4 Robustness tests

4.4.1 Replace variables

In order to mitigate the bias resulting from the measurement of single variables, we conducted a substitution of independent variables and re-evaluated the analysis. Specifically, we revised the measurement approach for BODT, shifting from a quantitative assessment based on the quantity of digital transformation keywords to a categorical evaluation. For instance, if we extract 10 digital transformation keywords from the relevant text of a company's annual report, with each keyword falling into one of two major categories, a value of 2 will be assigned. Additionally, recognizing the substantial variation in the extent of digital transformation across industries, we modified the measurement of DODT. Instead of calculating the ratio of a company's digital transformation keywords to the total number of digital transformation keywords across all companies in a given year, we computed the ratio of a company's digital transformation keywords to the total number of digital transformation keywords within its respective industry. The empirical findings subsequent to the substitution of variables are presented in Table 8. In panel A, the coefficients of digital transformation and IOCG exhibit a significant negative relationship, while the coefficients of BODT and OOCG demonstrate a significant positive association. The coefficients of DODT, although positive, do not reach statistical significance. In panel B, both ASR and USR exert a significant negative regulatory influence on the relationship between BODT/DODT and IOCG. In panel C, slack resources exhibit a significant negative moderating effect on the relationship between BODT/DODT and OOCG. Specifically, USR demonstrates a significant negative moderating effect on the relationship between BODT and OOCG, but does not exhibit a significant negative moderating effect on the relationship between DODT and OOCG. Overall, the empirical results

TABLE 7 Moderating regression (OOCG).

Variables	OOCG	OOCG	OOCG	OOCG
BODT	0.2614***	0.2443***		
	(0.0201)	(0.0178)		
DODT			811.2039***	745.8102***
			(97.7809)	(81.5810)
ASR	3.3017***		3.0360***	
	(0.4146)		(0.3954)	
USR		0.0841***		0.0657***
		(0.0236)		(0.0226)
BODT*ASR	−0.2638***			
	(0.0792)			
BODT*USR		−0.0124**		
		(0.0055)		
DODT*ASR			−819.3124**	
			(322.1464)	
DODT*USR				−33.3406***
				(19.0502)
Age	−0.5291***	−0.4875***	−0.5377***	−0.5006***
	(0.1143)	(0.1143)	(0.1146)	(0.1146)
Size	1.1368***	1.3153***	1.4134***	1.3620***
	(0.0368)	(0.0362)	(0.0367)	(0.0360)
Lev	0.5051**	0.8830***	0.5127**	0.8708***
	(0.2237)	(0.2602)	(0.2245)	(0.2611)
Roa	6.3205***	4.9509***	6.3795***	4.8490***
	(0.6935)	(0.6565)	(0.6937)	(0.6583)
Cashflow	1.6162***	1.2258**	1.5356***	1.1680**
	(0.5591)	(0.5573)	(0.5606)	(0.5589)
Growth	−0.3804***	−0.5291***	−0.3816***	−0.5378***
	(0.1203)	(0.1184)	(0.1208)	(0.1188)
Dual	0.1614*	0.1500*	0.1944**	0.1877**
	(0.0837)	(0.0838)	(0.0839)	(0.0840)
Board	0.5637**	0.6015**	0.5413**	0.5881**
	(0.2296)	(0.2298)	(0.2302)	(0.2303)
Indep	1.0465	1.1312	1.1059	1.2233
	(0.8038)	(0.8041)	(0.8057)	(0.8062)
Top1	−0.6311**	−0.7304***	−0.6734**	−0.7721***
	(0.2593)	(0.2593)	(0.2600)	(0.2600)
Soe	−0.0096	−0.0095	−0.0688	−0.0752
	(0.0897)	(0.0899)	(0.0898)	(0.0899)
Mpower	−1.2286***	−0.4580***	−1.2664***	−0.4652***
	(0.1784)	(0.1349)	(0.1786)	(0.1353)
_cons	−29.7769***	−28.7600***	−30.8037***	−29.8486***
	(1.0032)	(0.9969)	(1.0006)	(0.9953)
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	26,902	26,902	26,902	26,902
Adj-R^2	0.1367	0.1350	0.1323	0.1306

Note: ***, ** and * represent 1%, 5% and 10% significance levels, respectively.

subsequent to the substitution of explanatory variables are basically consistent with the above hypothesis testing results.

4.4.2 Adjust sample

To mitigate the abnormal impact of the COVID-19 outbreak that commenced in 2020, we excluded the observation data from that year. The empirical findings based on the revised sample are presented in Table 9. In panel A, the coefficient representing the relationship between digital transformation and IOCG is significantly negative at the 1% level, while the coefficient indicating their influence on OOCG is positively significant. In Panel B, slack resources exert a significant negative regulatory effect on the relationship between digital transformation and IOCG. In panel C, both ASR and USR exhibit a significant negative regulatory effect on the relationship between BODT and OOCG. Furthermore, ASR demonstrates a significant negative moderating effect on the relationship between DODT and OOCG, whereas USR does not exhibit a significant moderating effect on the relationship between DODT and OOCG. Overall, the empirical results following the adjustment of the sample align closely with the aforementioned hypothesis testing outcomes. Additionally, to further validate the robustness of the findings, we conducted an additional analysis by excluding the data from 2015, considering the financial crisis during that period, and on this basis, we also removed the data of 2020 for repeated verification. The results from both analyses remain basically consistent with the previous findings.

4.4.3 Instrument variable approach

To address the issue of endogeneity, we followed the approach outlined in refer to Breuer et al. (2018) and utilized agglomeration-level data, specifically the mean values of BODT and DODT for the same year in the same province, as instrumental variables (IV) in a 2SLS regression. The agglomeration layer data exhibits a significant correlation with the explanatory variables, but not a direct correlation with the explained variables, satisfying the instrumental variable requirements. The empirical findings subsequent to the use of instrumental variables are presented in Table 10. In panel A, both the coefficients of digital transformation and IOCG are significantly negative, while the coefficients of digital transformation and OOCG are significantly positive. In panel B,

TABLE 8 Replace variables.

Panel A: Variables	IOCG	IOCG	OOCG	OOCG
BODT	−0.6384***		0.4196***	
	(0.0366)		(0.0309)	
DODT		−1.1847***		0.0174
		(0.1232)		(0.1040)
Controls	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	26,902	26,902	26,902	26,902
Adj-R^2	0.1944	0.1881	0.1330	0.1270
Panel B: Variables	IOCG	IOCG	IOCG	IOCG
BODT	−0.8093***	−0.7998***		
	(0.0508)	(0.0448)		
DODT			−1.8021***	−1.6008***
			(0.1833)	(0.1578)
ASR	−5.1982***		−4.6172***	
	(0.5182)		(0.4633)	
USR		−0.2469***		−0.1779***
		(0.0296)		(0.0260)
BODT*ASR	1.1262***			
	(0.2096)			
BODT*USR		0.0838***		
		(0.0135)		
DODT*ASR			3.2237***	
			(0.6634)	
DODT*USR				0.1870***
				(0.0453)
Controls	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	26,902	26,902	26,902	26,902
Adj-R^2	0.1974	0.1966	0.1913	0.1896
Panel C: Variables	OOCG	OOCG	OOCG	OOCG
BODT	0.4919***	0.4895***		
	(0.0430)	(0.0379)		
DODT			0.3091***	0.0469
			(0.1549)	(0.1334)
ASR	3.3683***		3.2931***	
	(0.4381)		(0.3915)	
USR		0.0970***		0.0551**
		(0.0250)		(0.0219)
BODT*ASR	−0.5096***			
	(0.1772)			
BODT*USR		−0.0363***		
		(0.0114)		
DODT*ASR			−1.5798**	
			(0.5606)	
DODT*USR				−0.0122
				(0.0383)
Controls	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	26,902	26,902	26,902	26,902
Adj-R^2	0.1349	0.1335	0.1293	0.1272

(Continued in next column)

TABLE 8 (*Continued*) Replace variables.

Note: ***, ** and * represent 1%, 5% and 10% significance levels, respectively.

both ASR and USR demonstrate a significant negative regulatory effect on the relationship between BODT/DODT and IOCG. In panel C, both ASR and USR exhibit a significant negative moderating effect on the relationship between BODT/DODT and OOCG. Additionally, the Cragg-Donald Wald F statistic is considerably larger than 10, rejecting the null hypothesis of weak instrumental variables. Therefore, even after addressing the endogeneity issue using instrumental variables, the results remain robust.

5 Conclusion and discussion

5.1 Research findings

This study utilizes text analysis and OLS estimation to examine the impact of BODT/DODT on IOCG/OOCG within companies listed on the Shanghai and Shenzhen stock exchanges in China, covering the period from 2011 to 2020. Additionally, it investigates the moderating effect of USR/ASR. The findings are summarized as follows:

Firstly, digital transformation (BODT/DODT) exhibit a substantial negative influence on IOCG, whereas they demonstrate a significant positive impact on OOCG. This study reveals a "double-edged sword" effect, wherein digitization negatively affects the input side of greenization while positively influencing the output side. This finding shares similarities with previous research that has examined the U-shaped relationship between digitalization and greening at the micro-enterprise level (Peng et al., 2022), as well as the inverted U-shaped relationship

TABLE 9 Adjust sample (2011–2019).

Panel A: Variables	IOCG	IOCG	OOCG	OOCG
BODT	−0.2883***		0.2296**	
	(0.0188)		(0.0162)	
DODT		−846.3055***		655.9072***
		(79.4962)		(68.5722)
Controls	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	23,411	23,411	23,411	23,411
Adj-R^2	0.1952	0.1911	0.1372	0.1332
Panel B: Variables	IOCG	IOCG	IOCG	IOCG
BODT	−0.3875***	−0.3717***		
	(0.0269)	(0.0235)		
DODT			−1488.8800***	−1253.7870***
			(119.4481)	(99.4374)
ASR	−5.0085***		−4.9620***	
	(0.5235)		(0.5019)	
USR		−0.2385***		−0.2218***
		(0.0291)		(0.0280)
BODT*ASR	0.5799***			
	(0.1027)			
BODT*USR		0.0417***		
		(0.0073)		
DODT*ASR			3030.0650***	
			(390.1825)	
DODT*USR				156.4480***
				(22.8525)
Controls	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	23,411	23,411	23,411	23,411
Adj-R^2	0.1985	0.1976	0.1954	0.1938
Panel C: Variables	OOCG	OOCG	OOCG	OOCG
BODT	0.2846***	0.2593***		
	(0.0232)	(0.0203)		
DODT			794.1567***	732.9191***
			(103.1868)	(85.9090)
ASR	3.6042***		3.2877***	
	(0.4520)		(0.4335)	

(Continued on following page)

TABLE 9 (*Continued*) Adjust sample (2011–2019).

Panel A: Variables	IOCG	IOCG	OOCG	OOCG
USR		0.0850***		0.0621**
		(0.0252)		(0.0242)
BODT*ASR	−0.3321***			
	(0.0886)			
BODT*USR		−0.0148**		
		(0.0063)		
DODT*ASR			−771.3872**	
			(337.0642)	
DODT*USR				−29.7013
				(19.7434)
Controls	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	23,411	23,411	23,411	23,411
Adj-R^2	0.1395	0.1375	0.1353	0.1334

Note: ***, ** and * represent 1%, 5% and 10% significance levels, respectively.

(Dou and Gao, 2022). Additionally, some studies have verified these relationships at the macro level (Li et al., 2021; Xiang et al., 2022b). However, the aforementioned studies approach greenization as a unified concept or employ a single indicator, such as carbon emissions, to measure it, and then conduct nonlinear analyses. In contrast, our study adopts a deconstructive approach to analyze greenization in terms of its input and output aspects, and meticulously investigates the heterogeneity of the relationship between digital transformation and greenization in both dimensions.

Secondly, DODT has a stronger impact on corporate greenization compared to BODT. In interdisciplinary research that explores the intersection of digitalization and greenization, similar to corporate greenization, scholars often treat digital transformation as a holistic concept and give less attention to the difference between digital transformation models. While some literature does differentiate digitalization based on its breadth and depth (Blichfeldt and Faullant, 2021; Ye et al., 2022; Yang Z. et al., 2023), there is a lack of specific analysis regarding the influence of different modes on green development. To address this gap and build upon existing literature, we divide digitalization into breadth and depth, and subsequently examines and compares their respective impacts on corporate greenization. This analysis aims to enhance our understanding of the relationship between corporate digitalization and greenization.

Thirdly, slack resources alleviate the negative relationship between digital transformation and IOCG, and weaken the positive impact of digital transformation on OOCG. To date, several studies have examined various variables in their research. For instance, Chen and Hao (2022) have focused on board characteristics, while Wang et al. (2023d) have explored the effect of natural resource rent and anticorruption regulation. Additionally, Wang et al. (2023c) have investigated the impact of geopolitics. However, there is a limited amount of research that has delved into the moderating effect of slack resources. For example, Ying et al. (2023) discovered that organizational slack enhances the positive correlation between artificial intelligence and green total factor productivity. In contrast, our findings reveal a consistent negative moderating effect of slack resources on various main effects. This comparative perspective enhances our understanding of how idle resources influence a company's strategy and behavior. Moreover, it offers novel insights into the integration of corporate behavioral theory and agency theory, shedding light on the organic combination of these two theoretical frameworks.

Fourthly, ASR play a stronger moderating role than USR in the relationship between digitalization and greenization. Scholars have conducted research on the influence of these resources on corporate behavior (Zhu et al., 2022). For instance, Xie (2022) and Hernandez-Vivanco and Bernardo (2022) have specifically examined the impact of these resources on green behavior. However, there is currently a lack of comparative analysis regarding their moderating effect. Building upon this idea, we further expand the concept by categorizing slack resources into two types: USR and ASR. We then analyze their respective moderating effects on the relationships between BODT/DODT and IOCG/OOCG. This approach allows for a more comprehensive understanding of the distinct roles played by different categories of slack resources within an organization.

5.2 Policy implications

Our findings have significant implications for management practice. Firstly, it is crucial for governments and relevant departments to recognize the differentiated impact of digital

TABLE 10 IV in 2SLS.

Panel A: Variables	IOCG	IOCG	OOCG	OOCG
BODT	−0.6092***		0.3031***	
	(0.0379)		(0.0312)	
DODT		−6207.3320***		2012.9270***
		(357.9285)		(274.9518)
N	26,902	26,902	26,902	26,902
Anderson LM	3766.5190	1157.5950	3766.5190	1157.5950
Cragg-Donald Wald F	4377.4390	1209.0160	4377.4390	1209.0160
Panel B: Variables	IOCG	IOCG	IOCG	IOCG
BODT	−0.9714***	−7.8994***		
	(0.0861)	(1.1405)		
DODT			−28270.6200***	−10576.5400***
			(2944.9540)	(703.2226)
ASR	−6.5067***		−18.6414***	
	(0.7341)		(1.9307)	
USR		−3.7568***		−0.8192***
		(0.5384)		(0.0546)
BODT*ASR	1.9827***			
	(0.2885)			
BODT*USR		1.8222***		
		(0.2754)		
DODT*ASR			74,798.6300***	
			(8126.5880)	
DODT*USR				1655.1920***
				(122.7584)
N	26,902	26,902	26,902	26,902
Anderson LM	2003.1280	50.5370	120.5560	620.9880
Cragg-Donald Wald F	2162.9930	50.6020	121.0270	635.2830
Panel C: Variables	OOCG	OOCG	OOCG	OOCG
BODT	0.5079***	2.4112***		
	(0.0708)	(0.4899)		
DODT			14,484.7100***	3206.2960***
			(1905.4100)	(514.9436)
ASR	5.2027***		11.2895***	
	(0.6034)		(1.2491)	
USR		1.1108***		0.2293***
		(0.2313)		(0.0400)
BODT*ASR	−1.0734***			
	(0.2372)			

(Continued on following page)

TABLE 10 (*Continued*) IV in 2SLS.

Panel A: Variables	IOCG	IOCG	OOCG	OOCG
BODT*USR		−0.5364**		
		(0.1183)		
DODT*ASR			−38309.4400**	
			(5257.9700)	
DODT*USR				−453.2379***
				(89.8914)
N	26,902	26,902	26,902	26,902
Anderson LM	2003.1280	50.5370	120.5560	620.9880
Cragg-Donald Wald F	2162.9930	50.6020	121.0270	635.2830

Note: ***, ** and * represent 1%, 5% and 10% significance levels, respectively.

transformation on corporate green investment and output. This understanding should inform the development of targeted defense and incentive policies. Currently, most existing policies treat digital transformation as a unified concept and do not differentiate between the input and output aspects of greening from a dynamic perspective. However, digital transformation can simultaneously promote green output while inhibiting corporate investment in green resources due to resource exploitation and production capacity loss. In light of this, governments should actively promote the digital transformation of enterprises while simultaneously increasing corporate information disclosure and strengthening supervision of green resource utilization. For instance, tax incentives and other methods can be employed to encourage enterprises to undertake digital transformation.

Secondly, it is essential for governments and relevant departments to establish an evaluation system for enterprise digital transformation. This system can provide decision-making references for the implementation of incentive policies. As our study shows, DODT has a more significant impact on corporate green output than BODT. This finding suggests that companies can improve their green levels to a greater extent by focusing on deepening digital technology capabilities in specific areas and strengthening the in-depth integration of these technologies with corporate operations. Therefore, relevant decision-making departments should evaluate the depth of enterprise digital transformation and implement incentives in a focused manner based on the evaluation results.

Thirdly, enterprises should pay special attention to the role of slack resources in the impact of digital transformation on greening. Slack resources weaken the “crowding out” effect of digital transformation on green investment, implying that companies should maintain a reasonable level of remaining resources and leverage their diminished advantages during the process of digitalization and greening. For example, retaining some unused production equipment and idle resources can help companies respond to demand and market risks effectively. However, it is important to note that slack resources also weaken the promotion effect of digital transformation on green output. In this regard, strengthening internal controls can be an effective approach to enhance the positive impact of digital transformation. Furthermore, our study reveals that ASR have a stronger moderating effect than USR. This finding suggests that ASR is the key to understanding the extent to which digitalization negatively affects IOCG and positively promotes OOCG. Therefore, companies should focus on ASR rather than USR during the aforementioned process.

5.3 Limitations and future recommendations

This paper possesses certain limitations that can be addressed in future research. Firstly, regarding the research design, further enhancements are required in terms of variable classification and measurement, sample data, and research methodology. In this study, the core variables were solely categorized based on the application of digital technology and greenization input and output, with measurement conducted solely through text analysis, thereby neglecting alternative approaches. Future research endeavors could propose more precise dimension divisions and variable measurement methods by leveraging novel tools such as artificial intelligence and machine learning. Additionally, the sample data employed in this study originated exclusively from listed companies in China, thereby failing to reflect industry and national-level disparities. Subsequent research could integrate secondary data with firsthand questionnaires or case data. While our study primarily focuses on standardized quantitative analysis methods, it overlooks qualitative research methods that offer closer alignment with practical applications. Future research could incorporate qualitative comparative analysis (QCA) and case studies to supplement the findings.

Secondly, with regards to the research findings, further exploration is warranted regarding the mediating mechanisms and boundary conditions. On one hand, our attention was solely directed towards the direct impact of digital transformation on enterprise greening, without delving into the intermediary variables that exist between them. Future studies could investigate the influence mechanism through multiple pathways, encompassing both positive and negative aspects, drawing upon relevant theories and literature. This would enable the provision of more comprehensive explanations regarding how digitalization affects greenization. On the other hand, our focus was limited to the moderating role of organizational slack, neglecting the potential impact of other contextual factors. Subsequent research endeavors could select additional moderating variables at the firm, industry, or even national level, thereby facilitating a more comprehensive understanding of the boundary conditions surrounding the relationship between digitalization and greenization.

Thirdly, in terms of applicable contexts, it is imperative to consider a broader range of contexts and levels, as well as to assess the reliability and validity of the findings. The impact of digitalization on greenization is a significant topic that encompasses multiple disciplines and spans macro and micro levels. However, our focus has been limited to exploring the relationship between digital transformation and the greening of enterprises solely within the Chinese context at the enterprise level. Future studies should aim to expand the research context and level, allowing for comparisons of similarities and differences in research outcomes. This would contribute to the generation of new and enhanced knowledge regarding the relationship between digitalization and greenization. For instance, it would be valuable to examine the disparities between developing and developed countries in terms of the enabling effects of digitalization on greenization. Additionally, testing the applicability of the conclusions drawn in this paper to companies across various industries would further enrich the understanding of this relationship.

Finally, with regards to the theoretical tools employed, it is essential to reassess existing theories or frameworks. In this study, we discovered that the impact of digitization on greenization varies significantly across different dimensions, and that slack resources represent a “sweet burden” for their relationship. It is evident that the explanations of the relationship between digitization and greenization provided by the resource-based theory, the behavioral theory of the firm, and the principal-agent theory are insufficient and incomplete. Therefore, future research endeavors should aim to revise or integrate these theories based on more detailed empirical analyses conducted across multiple contexts. This would facilitate the establishment of a more robust foundation for advancing research in this area.

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

Author contributions

XX: Conceptualization, Funding acquisition, Investigation, Project administration, Supervision, Writing–original draft, Writing–review and editing. YQ: Data curation, Formal Analysis, Methodology, Validation, Writing–original draft, Funding acquisition, Writing–review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher’s note

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